Delay-locking: Unraveling Multiple Unknown Signals in Unknown Multipath

Mohamed Salah Ibrahim and Nicholas D. Sidiropoulos
Department of Electrical and Computer Engineering, University of Virginia, Charlottesville, VA
Email: {salah,nikos@virginia.edu}

***Abstract*—Given a mixture of co-channel user signals subject to frequency-selective multipath, sensed through an array of co-located antennas, how can we recover the user signals? This is a difficult problem, especially when some of the user signals are much weaker than others, and we know little about the transmitted signal properties. The setup is relevant in a number of settings, including non-cooperative communications, signal intelligence, passive radar using illuminators of opportunity, and convolutive speech and audio separation. This paper considers the problem of unsupervised signal recovery in unknown multipath and (possibly strong) multiuser interference. Leveraging the fact that multiple independently faded copies of each signal are received through distinct paths at different times, this paper shows that relative path delays and the user signals can be identified via canonical correlation analysis (CCA). CCA is a powerful statistical learning tool that can efficiently estimate a common subspace even in the presence of noise and strong co-channel interference. The proposed approach provides rigorous recovery guarantees, can tolerate strong co-channel interference and low signal-to-noise ratio, and is computationally tractable for practical implementation. Simulations reveal that the proposed approach achieves much better performance than independent component analysis, which is the only baseline that works under similar assumptions in this setting.**

I. Introduction

Given a mixture of co-channel user signals subject to frequency-selective multipath, sensed through an array of co-located antennas, how can we recover the user signals? The setup is relevant in a number of settings, including non-coherent communication [1], cognitive radio (overlay) networks [2], non-cooperative / adversarial communications and signal intelligence, passive radar using illuminators of opportunity [3], and convolutive speech and audio separation [4].

In wireless communications, multipath refers to the reception of multiple independently faded and delayed copies of the original transmitted signal [5]. On one hand, multipath components introduce inter-symbol interference which together with the co-channel interference that arises from multiple users represent two major obstacles that can severely degrade the detection performance [5]. On the other hand, if the different paths can be coherently combined, multipath can lead to significant diversity gain and/or multiplexing gain [6], [7]. In this paper, we show that multipath can be exploited in an entirely new way: it can be used to directly recover each of the unknown signals, by looking for multichannel data shifts that exhibit high *canonical correlation* – they contain a common subspace after alignment, which would otherwise be absent without such alignment because the emitted user signals are white, and thus are uncorrelated with their own shifts.

Most work in multiuser signal detection assumes accurate knowledge of the user channels or essential propagation parameters, such as path delays and Doppler shifts [1], [8]. These approaches rely on user cooperation and training symbols / pilots to estimate the channels of interest. These are supervised approaches that are widely used in cellular and other commercial systems, but they are not applicable in the non-cooperative / unsupervised settings considered herein. So-called *blind* convolutive signal separation techniques are in principle applicable in our context, but require that the emitted signals have certain known structural properties [9]–[11]. In a wireless communication setting (and certain other contexts, such as speech signal separation) [12], [13], a natural assumption is statistical independence of the signals corresponding to the different users, leading to independent component analysis (ICA)-based algorithms [14], [15]. One common shortcoming in all the methods considered in the aforementioned works, including ICA, is that they require high signal-to-noise ratio ($> 25-30$ dB) in order to provide reasonably good performance. This motivates us to ask whether there exists a low-complexity approach for the given problem that can reliably detect source signals under the following circumstances 1) low SNR, 2) no knowledge about the channel 3) strong and unknown co-channel interference? This is the central question that this paper seeks to address.

Exploiting the fact that multiple copies of the same information bearing signal are received through different paths, and thus multiple copies of the same signal arrive at different times, this paper shows that reliable source signal recovery is possible via canonical correlation analysis (CCA) [16] – a statistical learning tool that aims at estimating a common subspace via eigendecomposition. Under the assumption that different users have distinct relative delay profiles, we first develop a low-complexity CCA-based algorithm that can identify the relative delay between the received paths of each user. Then, we exploit such delays to construct K matrix pairs – one pair for each co-channel user in the system. The common component in each pair corresponds to the transmitted signal of a specific user whose relative delay is used to construct that pair. We apply CCA K times to recover the common signal included in each pair. An identifiability proof of the common signal recovery via CCA has been established by the authors in [17]. Judicious experiments demonstrate the efficacy of the proposed approach in recovering the original

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transmitted user signals even at low SNR and strong co-channel interference. In particular, our CCA-based approach attains an order of magnitude reduction in the bit error rate (BER) compared to ICA under realistic conditions. Finally, the paper includes a brief discussion on why the proposed method can recover signals received at low SNR.

While CCA has previously found numerous signal processing applications including direction-of-arrival (DoA) estimation [18], equalization [19], blind source separation [20], and multi-view learning [21], it has never been used for our purpose (blind recovery of weak signals under strong interference) or in a way that is reminiscent of how we bring it into play, to the best of our knowledge. In addition, previous applications of CCA did not lay down any claims regarding identifiability guarantees and performance analysis in the presence of noise, as we do.

II. Data Model

We consider a non-cooperative wireless communication scenario here, which is appropriate for signal intelligence and cognitive overlay scenarios, but our signal model is quite generic – it can be applied to convolutive speech separation, for example. Also, since we use binary communication signals in the simulations, we use BER as performance measure, but our approach can work with higher-order modulations and even analog signals.

Consider K single-antenna users transmitting in a specular multipath environment. The signals are received by a base station (BS) equipped with M antennas. The n-th sample of the transmitted signal of the k-th user, $s_k(n)$, is received over L_k distinct paths, for $n \in [N] := \{1, \cdots, N\}$ and $k \in [K] := \{1, \cdots, K\}$. Considering K asynchronous users, the M-dimensional received baseband signal at the BS is given by

$$\mathbf{x}(n) = \sum_{k=1}^{K} \sum_{\ell=1}^{L_k} \alpha_{k\ell} s_k(n - \tau_{k\ell}) \mathbf{a}(\theta_{k\ell}) + \mathbf{w}(n) \qquad (1)$$

where $\tau_{k\ell} \in [0, 1, \cdots, \tau_{k,\text{max}}]$ is the (relative) delay- expressed in sample bins- of the ℓ-th path associated with the k-th user, $\tau_{k,\text{max}}$ is the delay spread of the k-th user channel, $\alpha_{k\ell} = \beta_{k\ell} e^{j\phi_{k\ell}}$ is the complex path gain, $\theta_{k\ell}$ is the angle of arrival at the receiver, and $\mathbf{w}(n) \in \mathbb{C}^M$ contains independent identically distributed (i.i.d) entries with each element drawn from a complex Gaussian distribution with zero mean and variance σ^2. The term $\mathbf{a}(\theta)$ models the array response to a path from a direction of arrival θ. It is assumed that the array response and all the channel parameters are not known at the receiver.

Assume that the receiver collects T samples of the data and forms $\mathbf{X} = [\mathbf{x}(1), \cdots, \mathbf{x}(T)] \in \mathbb{C}^{M \times T}$, with T such that the channel varies negligibly over the collected samples. Throughout this paper, we have the following assumptions

- The number of observed samples T is greater than $N + L^*$, where
$$L^* = \max_k \tau_{k,\text{max}} \qquad (2)$$
- All the relative delays between paths of different users are assumed to be distinct. That is,
$$\{\tau_{ki} - \tau_{kj}\}_{i,j=1}^{L_k} \neq \{\tau_{k'i'} - \tau_{k'j'}\}_{i'j'}^{L'_k} \qquad (3)$$

$\forall\ k, k' \in [K]$ and $k \neq k'$.

Remark 1. *If the number of dominant paths is small, then the second assumption will be satisfied with very high probability. In this case, our approach does not have any restriction on the entries of the transmitted signals of the users (see Theorem 1). However, if it happens that the condition in* (3) *is violated, then our approach will identify the range space of the signals that share the same relative delay, and thus an extra stage will be required to identify the signals from the given mixture provided that they belong to finite alphabet [17].*

In what follows, we will propose a low-complexity learning-based method that can blindly recover the k-th user signal $\mathbf{s}_k = [s_k(1), \cdots, s_k(N)] \in \mathbb{R}^N$, with $\|\mathbf{s}_k\|^2 = 1$ for $k \in [K]$, without any knowledge of the users channels.

III. Signal Detection Via CCA

Let us first transform the received signal $\mathbf{X}$ to the real domain by forming the matrix $\overline{\mathbf{X}} = [\mathbf{X}_r; \mathbf{X}_i] \in \mathbb{R}^{2M \times T}$, where $\mathbf{X}_r = \mathbb{R}\text{e}\{\mathbf{X}\}$ and $\mathbf{X}_i = \mathbb{I}\text{m}\{\mathbf{X}\}$ are the real and imaginary parts of the received signal $\mathbf{X}$. Assuming that the sequence length N is known at the receiver, the main goal is to recover the signals $\{\mathbf{s}_k\}_{k=1}^K$ given $\overline{\mathbf{X}}$.

In a recent work [17], we showed that if two signal matrices contain one shared (common) component and multiple individual components at each one, then CCA can efficiently extract the common component possibly with a sign flip regardless how strong the individual components are. Building upon [17], we will present a novel two-stage CCA based technique that can identify the transmitted signal and the relative delay between the received paths of each user. Note that, we assume here for simplicity of treatment that the number of dominant paths is equal to two for all users, i.e., $L_k = 2\ \forall k$, however, the general case of $L_k > 2$ will be included in the journal version.

A. Relative Delay Identification

Given the data matrix $\overline{\mathbf{X}}$, we construct the following two matrices

$$\mathbf{X}_1^{(m_1)} := [\overline{\mathbf{x}}(m_1), \cdots, \overline{\mathbf{x}}(N + m_1 - 1)] \qquad (4)$$

$$\mathbf{X}_2^{(m_2)} := [\overline{\mathbf{x}}(m_2), \cdots, \overline{\mathbf{x}}(N + m_2 - 1)] \qquad (5)$$

where $\mathbf{X}_\ell \in \mathbb{R}^{2M \times N}$ and $\overline{\mathbf{x}}(t) \in \mathbb{R}^{2M}$ denotes the t-th column of the matrix $\overline{\mathbf{X}}$, for $t = 1, \cdots, T$. Upon fixing m_1 and varying m_2 over a window of size $T - N$, we solve the following problem at each value of m_2,

$$\min_{\mathbf{q}_1, \mathbf{q}_2} \ \|\mathbf{X}_1^T \mathbf{q}_1 - \mathbf{X}_2^T \mathbf{q}_2\|_F^2 \qquad (6a)$$

$$\text{s.t.} \quad \mathbf{q}_\ell^T \mathbf{X}_\ell \mathbf{X}_\ell^T \mathbf{q}_\ell = 1, \quad \ell = 1, 2 \qquad (6b)$$

where we dropped the dependence of $\mathbf{X}_1$ and $\mathbf{X}_2$ on m_1 and m_2, respectively, for notational convenience. Problem (6) is known as the distance minimization formulation of the two view CCA [22]. It aims at minimizing the distance between two linear transformations of the data in each view [16]. In other words, it finds two canonical vectors $\mathbf{q}_1 \in \mathbb{R}^{2M}$ and $\mathbf{q}_2 \in \mathbb{R}^{2M}$, such that the correlation between the projections of $\mathbf{X}_1$ and $\mathbf{X}_2$ onto these directions is maximized. It has been shown that (6) admits a simple algebraic solution via eigendecomposition [22].

Exploiting the fact that the k-th user transmitted signal is uncorrelated over the time, and hence, two replicas of the same user signal shifted by even one symbol are already uncorrelated, its signal cannot be extracted via canonical correlation analysis as long as $\mathbf{X}_1$ and $\mathbf{X}_2$ are misaligned. In other words, the correlation coefficient measured at each shift m_2 will not attain its peak unless we hit the correct delay between the two paths of each user. Furthermore, since different users are assumed to have different relative delays, we will get K distinct peaks; each of which corresponds to finding a direction where the linear projections of $\mathbf{X}_1$ and $\mathbf{X}_2$ are maximally correlated.

Let $\rho(m_2)$ denote denotes the correlation coefficient associated with the optimal canonical pair $(\mathbf{q}_1, \mathbf{q}_2)$ resulting from solving (6) for $m_2 = 1, \cdots, T-N$. Assume that the receiver stores the value of ρ for all iterations. After solving (6) $T-N$ times, we pick the K largest correlation coefficients and the corresponding m_2 values. This procedure is summarized in Algorithm 1.

Remark 2. *The value of m_1 is chosen such that $\mathbf{X}_1^{(m_1)}$ contains a sufficient number of samples received according to* (1). *This is guaranteed with a very high probability as long as $T-(N+L^*) \ll (N+L^*)$. One possible choice is to set $m_1 = T/2 - N/2$ so that one can assure the existence of enough samples from all users in $\mathbf{X}_1$.*

Algorithm 1 Delay Locking Via CCA

Input: $\overline{\mathbf{X}} \in \mathbb{R}^{2M\times T}$
Initialization: $m_2 := 1$
while $m_2 \leq T-N$ **do**
  Compute ρ after solving (6) using $\mathbf{X}_1^{(m_1)}$ and $\mathbf{X}_2^{(m_2)}$ from (4)-(5)
  Store (m_2, ρ) in a stack
  Set $m_2 := m_2 + 1$
end
Selection: pick the K m_2 values corresponding to the highest K correlation coefficients ρ.

The receiver now can identify the relative delay, $\tau_k^* = |m_2 - m_1|, \ \forall\, k \in [K]$, using the stored values of m_2. Solving (6) is equivalent to solving for a principal eigenvector [22] which can be cheaply computed via the power method.

B. Signal Recovery Via CCA

We will now discuss how the user signals can be identified given the relative delays between the paths of all users. Let us consider the computed relative delay τ_k^* of the k-th user, then by setting $m_1 = 1$ and $m_2 = m_1 + \tau_k^*$, the matrix $\mathbf{X}_{k\ell}$ can be written as

$$\mathbf{X}_{k\ell} = \mathbf{h}_{k\ell}\mathbf{s}_k^T + \sum_{j\neq k}^{K} \mathbf{h}_{j\ell}\mathbf{s}_{j\ell}^T + \mathbf{W}_{k\ell} \tag{7}$$

where $\mathbf{h}_{i\ell} \in \mathbb{R}^{2M}$ is the i-th user channel vector in the real domain, for $i \in [K]$, and $\ell = 1,2$ is the path number. We can write (7) in a more compact form as

$$\mathbf{X}_{k\ell} = \mathbf{h}_{k\ell}\mathbf{s}_k^T + \mathbf{H}_{k\ell}\mathbf{S}_{k\ell}^T + \mathbf{W}_{k\ell} \tag{8}$$

where $\mathbf{S}_{k\ell} \in \mathbb{R}^{N\times(K-1)}$ contains the $K-1$ source signals associated with the ℓ-th path (view) when the k-th user is synchronized, and $\mathbf{H}_{k\ell} \in \mathbb{R}^{2M\times(K-1)}$ holds on its columns the respective channel vectors. Note that by the assumption in (3), we can not have more than one synchronized user.

Remark 3. *Note that setting $m_1 = 1$ assumes that the first path of the k-th user arrives at the first sample in the sequence $\overline{\mathbf{X}}$ which is not true in general. However, from the practical point of view, each user has its own identification sequence as a preamble, so once we know the correct relative delay, we can simply find the sample index at which the first path arrives via correlation with the identification sequence of the k-th user.*

To see how can we utilize CCA to identify the signal $\mathbf{s}_k$ from $\mathbf{X}_{k1}$ and $\mathbf{X}_{k2}$, $\forall\, k \in [K]$, we will use an equivalent formulation to that of (6) in the sense that both of them yield the same optimal solution $\mathbf{q}_\ell^*$ in the two view (path) case. That is,

$$\min_{\mathbf{g},\mathbf{q}_1,\mathbf{q}_2} \sum_{\ell=1}^{2} \|\mathbf{X}_{k\ell}^T\mathbf{q}_\ell - \mathbf{g}\|_F^2 \tag{9a}$$

$$\text{s.t.} \quad \|\mathbf{g}\|_2^2 = 1 \tag{9b}$$

The above problem is known as the MAX-VAR formulation of the CCA [22]. It seeks to find a direction $\mathbf{g} \in \mathbb{R}^T$ that is maximally correlated after the linear projections of $\mathbf{X}_{k1}$ and $\mathbf{X}_{k2}$ on $\mathbf{q}_1$ and $\mathbf{q}_2$, respectively. The following theorem, which is a slight modification of the results of [17], states the conditions for identifying the transmitted signal $\mathbf{s}_k, \forall k$.

Theorem 1. *Free from noise, if matrix $\mathbf{B}_k := [\mathbf{s}_k, \mathbf{S}_{k1}, \mathbf{S}_{k2}] \in \mathbb{R}^{N\times(2K-1)}$ is full column rank, and $\mathbf{Z}_{k\ell} = [\mathbf{h}_{k\ell}, \mathbf{H}_{k\ell}] \in \mathbb{R}^{2M\times K}$ is full column rank for $\ell \in \{1,2\}$, then the optimal solution $\mathbf{g}^\star$ of problem* (9) *is given by $\mathbf{g}^\star = \gamma\mathbf{s}_k$, where $\gamma = \pm 1$.*

Proof. The proof is provided in Theorem 1 in [17]. □

Remark 4. *The assumption that different users have distinct relative delays allows us to identify one user at each time. This removes the restriction we have in Theorem 1 in [17] of having the transmitted sequences belong to finite alphabet.*

We outline all the steps needed to recover all user signals in Algorithm 2. The overall complexity of Algorithm 2 depends on the cost required for solving Algorithm 1 and problem (9). Since problem (9) can be optimally solved using a power iteration, it follows that the overall approach

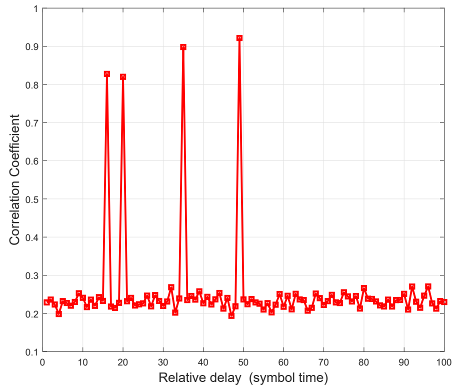

Fig. 1: Relative delay versus correlation coefficient, with $K = 4$, $M = 6$

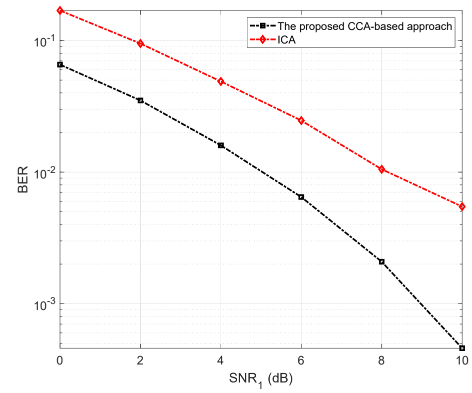

Fig. 2: BER vs. SNR of the first path, with $K = 4$ and $M = 6$

Algorithm 2 Signal Detection Via CCA

Input: $\overline{\mathbf{X}} \in \mathbb{R}^{2M \times T}$
Initialization: $k := 1$
while $k \leq K$ **do**
  Compute τ_k via Algorithm 1
  Construct $\mathbf{X}_{k1}$ and $\mathbf{X}_{k2}$ using τ_k as in (7)
  Solve problem (9) by using $\mathbf{X}_{k1}$ and $\mathbf{X}_{k2}$ as an input
end

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requires using the power method $K(T - N + 1)$ times. This renders our approach computationally tractable for practical implementation.

C. Noisy Case

In [23], we have carried out a performance analysis that shows how CCA can identify signals in the presence of noise and even if the signals are received at low SNR. Although the analysis was performed for an entirely different application, the result can be easily mapped to the problem considered here. In a nutshell, under some assumptions, we managed to relate the correlation coefficient associated with the optimal canonical pair to the relative SNR of each user at different views (different paths here). In the ideal case, if there exists a common component, then the correlation coefficient will be equal to one. On the other hand, when the noise is present, the correlation coefficient will be affected due to the addition of different noise at different views. By mapping our result in [17] to the problem considered here, the correlation coefficient between $\mathbf{X}_{k1}\mathbf{q}_1$ and $\mathbf{X}_{k2}\mathbf{q}_2$ when the k-th user signal is synchronized is given by

$$\rho_k = \frac{\gamma_{k1}\gamma_{k2}}{(\gamma_{k1} + 1)(\gamma_{k2} + 1)} \tag{10}$$

where $\gamma_{k\ell}$ is the received SNR of the ℓ-th path of the k-th user, for $\ell = 1, 2$. Note that the higher the correlation coefficient, the higher the probability we can identify the common signal. Equation (10) shows that as long as the path powers are few dBs above the noise, one can get a reasonable value for the correlation coefficient. For example, $\gamma_{k1} = 5$dB and $\gamma_{k2} = 8$dB will lead to a $\rho_k \approx 0.7$. This reflects how the proposed approach can identify the user signals even if they are received at low SNR. Furthermore, our approach can detect the user signals no matter how far the received SNR of the two paths from each other. For example, $\gamma_{k1} = 15$dB and $\gamma_{k2} = 5$dB will lead to a $\rho_k \approx 0.75$.

IV. Experimental Results

To evaluate the performance of our proposed method, we consider a scenario with four single-antenna users transmitting binary signals of length $N = 1000$ to a single receiver equipped with $M = 6$ antennas. The arrival time, τ_{1k}, of the first path of the k-th user follows a uniform distribution, i.e., $\tau_{1k} \sim \mathcal{U}[1, 2, \cdots, 20]$ while the arrival time, τ_{2k}, of the second path of the same user was selected as $\tau_2 \sim \mathcal{U}[30, 31, \cdots, 60]$. In the simulation, we enforced the relative delay $\tau_k = \tau_{2k} - \tau_{1k}$ to be different for all $k \in [K]$. Additive white Gaussian noise is added with variance σ^2 so that the SNR is P_1/σ^2, where P_1 is the first path received power. Note that we assumed that P_1 is fixed for all users while the second path received power was set to $P_{2k}(\text{dBm}) = P_1(\text{dBm}) - P_{dk}(\text{dB})$, where $P_{dk} \sim \mathcal{U}[2, 4]$ in dB. We assume that the receiver collects $T = 1100$ samples. All results were averaged over 500 channel realizations.

In order to benchmark the performance of our proposed method, we used the so-called independent component analysis (ICA) [14] – a well-known blind source separation technique that can extract independent source signals from a given mixture. We have directly used the fastICA MATLAB codes written by the author of [14].

In a preliminary experiment, we first tested Algorithm 1 to see how the relative delays of all users can be identified. We fixed the SNR of the first path, i.e., SNR$_1$, for all users to 6dB while the SNR of the second path is different across different users according to the relation mentioned before. Figure 1 depicts how Algorithm 1 can efficiently identify the relative delay for all users. Obviously, when all the user signals are misaligned, the correlation coefficient is very low compared to the case when any of the users signals is aligned. Furthermore, the assumption that all relative delays are distinct allows us to see distinct peaks for the correlation coefficient. Recall that our approach can also deal with identical relative delays using finite alphabet [17].

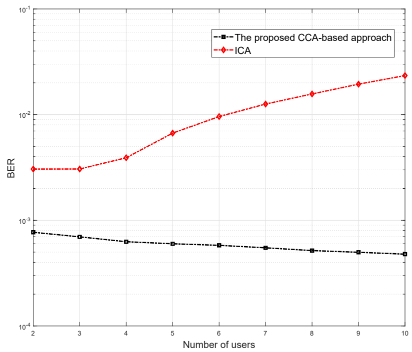

Fig. 3: BER vs. number of users (K), where for each value of K (number of users) we set the number of receive antennas $M = 2K$.

We now consider another experiment where we vary the SNR of the first path from zero to 10dB and at each value we compute the average BER for the proposed method and ICA. In figure 2, we observe that our proposed CCA-based approach considerably outperforms the ICA one in terms of BER, where an order of magnitude improvement in BER was observed at $\text{SNR}_1 = 10\text{dB}$.

Finally, we simulated another experiment by varying the number of users, K, from 2 to 10 and at each value of K we set the number of antennas $M = 2K$, i.e., at $K = 2$ we use 4 antennas while at $K = 10$ we use 20 antennas. Furthermore, we fixed the SNR of the first path to SNR $= 8$dB. Figure 3 shows how our approach can efficiently work under strong interference. It is obvious that the BER achieved by our method is approximately the same for different number of users while the BER attained by ICA degrades by approximately order of magnitude at $K = 2$ compared to $K = 10$. It is worth pointing that the slight decrease in the BER obtained by the proposed method is due to the fact that we double the number of antennas at each value of K which in turn leads to more reduction in the noise after using CCA [23]. In addition, the result in Figure 3 suggests that the proposed approach can handle dense massive MIMO uplink scenarios.

V. Conclusions

This work has studied the problem of unsupervised signal detection in a multipath environment. We first developed a low-complexity CCA-based algorithm that can efficiently identify the relative delays between the user paths. Then, we exploited CCA to recover the users transmitted signals using the relative delay. Furthermore, we provided a brief discussion that shows how our approach can still work even if the user signals are received at low SNR. This in fact opens new opportunities for more aggressive frequency reuse and secondary spectrum usage. Simulations revealed that our unsupervised CCA method achieves more than an order of magnitude improvement in the BER compared to other unsupervised signal separation techniques. In particular, we showed how our approach can efficiently decode different user signals in the presence of noise and strong co-channel interference.

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